CLASSIFICATION OF ELECTROCARDIOGRAM USING SOM, LVQ AND BEAT DETECTION METHODS IN LOCALIZATION OF CARDIAC ARRHYTMIAS

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Abstract - **The work investigates a set of efficient methods to extract important features from the ECG data applicable in the localization of cardiac arrhythmia. The work involves the segmentation of the ECG signal and the extraction of important features like QRS and ST segments. Further classification follows the learning process where the SOM (Self Organizing Maps) units organize in such a way that similar map sequences of the ECG data are represented in particular areas of the SOM. Eventual unsupervised learning (UL) time traces are achieved during the training and forwarded to the LVQ (Learning Vector Quantization). Here a set of supervised learning (SL) is followed by a smart beat detection system that further enhances the signal performance and correct localization for arrhythmia detection.**

Keywords: **ECG, SOM, LVQ, Beat Detection**

I. INTRODUCTION

The electrocardiogram carries a lot of clinical information for a cardiologist, especially the width or duration of the waves in the ECG are widely used to define conduction in the heart and to stratify patients at risk of cardiac arrhythmia [2][3]. The manual annotation to the waves is a strenuous task, as a result several automated methods have been developed to relieve the cardiologist.

The QRS complex duration is an important parameter employed in the analysis and classification of the ECG signal. This parameter is defined as the time it takes for depolarization of the ventricles. Normal depolarization requires normal functioning of the right and left bundle branches, delayed depolarization of the ventricles due to the blocked bundle branches varies from 0.04 to 0.09 seconds. In abnormal case the QRS interval is 0.1 s or more [8]. The ST segment is also an important indication in the diagnosis of myocardial ischemia. For this reason the measurements taken on the ST segment forms a predominant factor in the interpretation phase of the ECG. The recognition of the ST segment poses a serious problem in those cases where the ST segment and the T wave are fused together and makes it difficult to identify the fiducial points. The smart detection system takes care of such artifact [7].

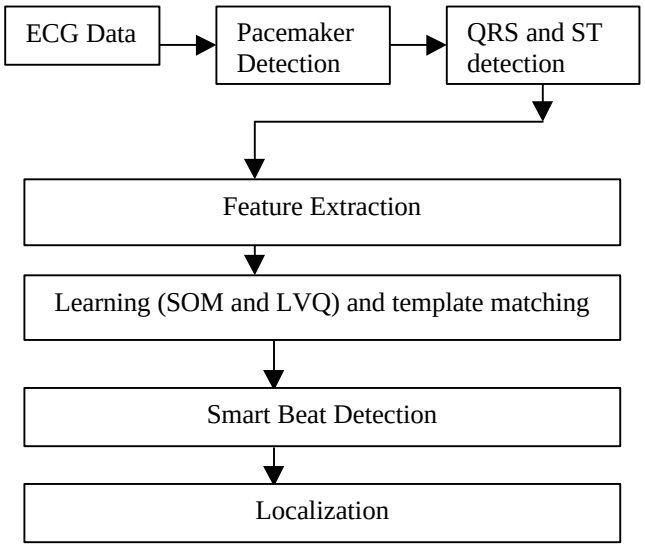

Fig 1: Analysis and classification process

The block diagram represents the basic sequence of the study. The acquired data is first tried for pacemaker detection. Then the QRS and ST segment data are detected and classified and features are extracted using separate filters. This follows the UL of the SOM [1][4] and the SL of the LVQ. The smart detection technique determines the wave peak amplitudes that detect the probabilistic values before a localized result is obtained.

II. METHODS AND RESULTS

The ECG data is digitizing at a frequency of 16KHZ to detect the pacemaker pulses digitally. The signal is then downsampled to 250 Hz. At this point the data is allowed to pass through a bandpass filters at 0.16 Hz - 300 Hz. One filter is used for QRS and ST detection and one filter is used for QRS and ST classification. This detection filter removes low frequency.

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Abstract

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A. SOM training

Altogether, 33 recordings were obtained from 10 different patients during catheter pace mapping were used to train the Self-Organizing Map. From each recording, three representative QRS and ST complexes were selected. The selected QRS and ST complexes were sampled at 5 ms interval and suitably resealed [5]. This resulted in more than 1500 different potential maps. The scaled maps were then used as input for further processing. In this study the input structure for the Self organizing is based on sampled QRS and ST complexes obtained from recordings during ventricular pacing. Every cell on the SOM represents a potential map on the body surface. Due to the limitation of four pages, only QRS complex recordings can be discussed.

A parametric reference vector mi is associated with every node. A data vector x is compared to all reference vectors in any metric and the best matching node is defined, e.g., by the smallest Euclidean distance between the data vector and any of the reference vectors. During learning, those nodes that are topographically close in the array up to a certain distance will activate each other to learn from the same input,

mi(t + 1) = mi(t) + hci(t)[x(t) - mi(t)]

where t is an integer representing time, and $h_{ci}(t)$ is the so called neighborhood kernel describing the neighborhood that is updated around the best-matching node. Several suitable kernels can be used, e.g. a so-called bubble kernel or a gaussian kernel, relating to different ways of determining the activating cells. The kernel also includes the learning rate parameter $\alpha(t)$.

The development of a SOM during the learning process is shown in Fig 2. After random initialization of the reference vectors (initial phase), self-organization of the map starts (middle phase), and spreads over the network (final phase).

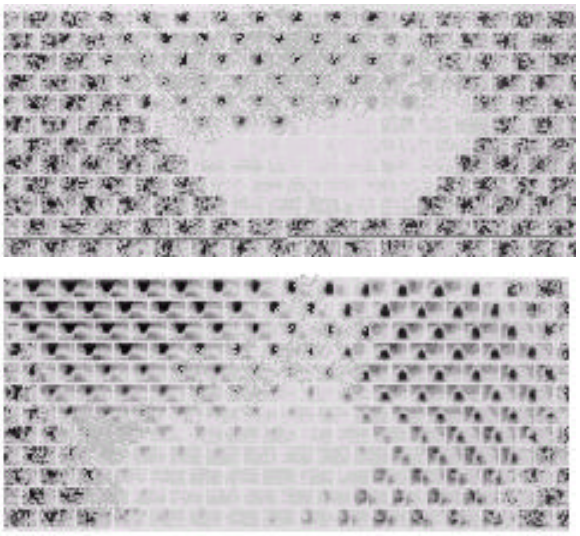

Fig 2: SOM development during training Initialization (initial phase), 120 epochs (middle phase) and 1375 epochs (final phase)

The organization of a fully trained SOM is presented in Fig. 3 (top phase). The zero was fixed to the center of the SOM. It is demonstrated that the map direction is changing smoothly on the SOM. In all teaching runs, the SOM organized to a good quality representation of the endocardium i.e. adjacent points on the endocardium mapped to adjacent points on the SOM. Moreover, the fully trained SOM do not include any meaningless or random maps. Of all teaching runs, the SOM that resulted in the lowest quantization error of the test set was chosen to be used in the classification.

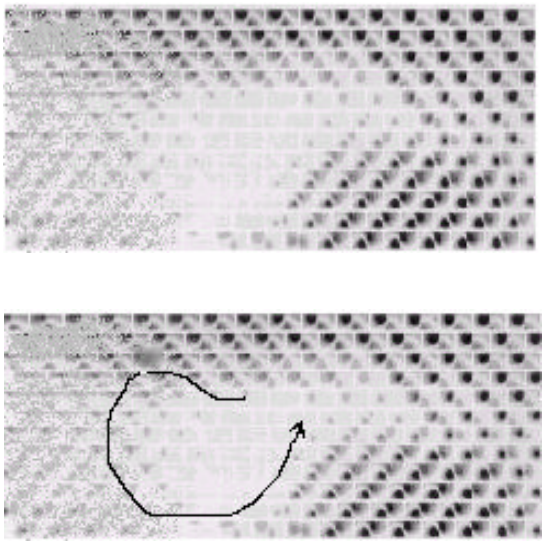

Fig 3: Fully trained SOM (top), QRS trajectory of a paced ventricular beat on SOM (bottom)

B. QRS Trajectories on the SOM

When a new potential map is presented to the trained SOM, the matching node is found. Tracing the best matching nodes for potential maps during the paced QRS results in a trajectory on the SOM units, as shown in Fig. 3.

C. LVQ Input

The time tracings of the paced beats on the SOM were quantified for subsequent localization of the pacing site as follows: For each node of the SOM the shortest distance between the codebook vector associated with that node and the data vectors of the given sequence were calculated. After logarithmic scaling a distribution of distances over the SOM is obtained. This distribution in the following is referred to as QRS distance map. Two QRS and ST distance maps from different pacing locations are presented

In Fig. 4 bright nodes are closer to a particular sequence data vector from the sequence than dark nodes. The distance maps of all paced beats are used as input for a LVQ classifier.

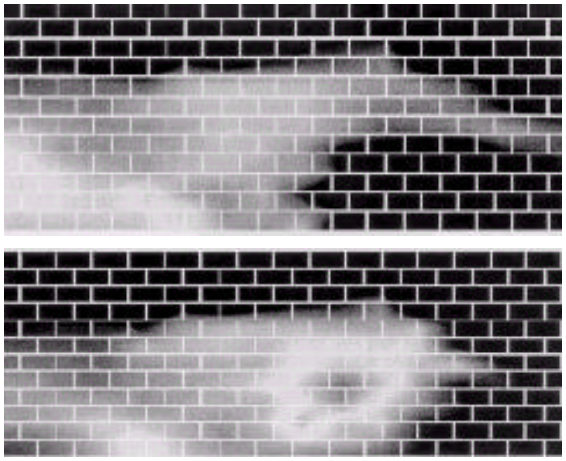

Fig 4: QRS distance maps of two paced beats from different locations of the heart

D. LVQ Classification and Localization

In the LVQ algorithm, vector quantization is used to directly define the class borders according to the nearest neighbor rule [5]. The accuracy of the LVQ classification depends on the number of codebook vectors assigned to each class as well as on the proper learning rate.

The accuracy of LVQ classification for different pacing locations is shown in Table I. The pacing locations (L1-L17) is used in this study were similar to those defined by Josephson et al. [6]. The position of the catheter was controlled by biplane fluoroscopy. An overall accuracy of 77.1% for the correct pacing location was achieved. It has to be taken into account that also adjacent pacing sites provide a useful first estimation of the pacing location.

III. Smart Beat Detection

The established knowledge base is used along with the pre-feeded data of width, polarity, shape, ST duration, St area and R-R interval etc. Probabilistic comparison is done which determine the normal and abnormal beat. The patient's CDB was 100ms and the incoming beat was 120ms. The normal beat width would be 120/100=1.2. For a normal beat a probability of 56% was obtained which is normal and a probability of 84% was obtained for ventricular beats. Each of the probabilistic values are determined for each parameter. The class with the highest likelihood is considered as the final class.

TABLE I

PACING LOCATION	NUMBER OF PACED BEATS	RECOGNITION ACCURACY %
LI	19	49
L2	19	50.2
L3	7	49.1
L4	15	93
L5	3	99
L6	10	100
L8	3	100
L9	8	75.1
L12	19	33.7
L17	20	100
L19	22	100
ALL	145	77.1

IV. Conclusion

We have developed a novel method for arrhythmia localization from potential mapping data. The QRS integral maps that display only spatial information are based on the whole QRS complex, the SOM and LVQ approach uses both spatial and temporal QRS-Information, and we believe this may result in

a better localization accuracy. The method is fast, and the SOM used for localization can be upgraded easily. Moreover, the method performs in a predictable manner for new beats falling between the teaching beat, which is a behavior similar to that, of the QRS integral method. The Smart beat detection system aims to obtain for each paced beat a probability distribution describing likelihood that it belongs to a particular pacing location. Thereby removing the doubts of mixing a P wave with a T wave where sharper and flatter peaks matter etc.

V. ACKNOWLEDGEMENT

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